Appendix A. Defining Major Categories

To aggregate the almost 400 four-digit majors of the CIP taxonomy into a smaller set of 70 aggregated categories (hereafter referred to as *final major*), we start with the CIP's aggregation of four-digit majors (cip4) into 49 two-digit major codes (cip2). We omit from our categorization 14 two-digit categories that are traditionally sub-baccalaureate or remedial programs (Interpersonal and Social Skills (cip2=35), Basic Skills and Developmental/Remedial Education (32), Citizenship Activities (33), Health-Related Knowledge and Skills (34), Personal Awareness and Self-Improvement (37), High School & Secondary Diplomas and Certificates (53)); that are predominantly post-baccalaureate or graduate programs (Residency Programs (60)); that are predominantly trade-specific and usually sub-BA (Science Technologies/Technician (41), Construction Trades (46), Mechanic and Repair Technologies/Technicians (47), Precision Production (48), and Transportation and Materials Moving (49)); or that operate in separate or specific labor markets (Military Science, Leadership, and Operational Art (28) and Military Technologies and Applied Sciences (29)). Together these categories comprise less than 1% of all degrees granted by four-year postsecondary institutions over the 2010–2017 period and appear on less than 0.1% of job postings in our analytic sample. For similar reasons we also omit particular four-digit majors (not already in omitted two-digit categories) that are primarily sub-baccalaureate or graduate programs, including Funeral Service and Mortuary Science (1203), Cosmetology and Related Personal Grooming Services (1204), Medical Clinical Sciences/Graduate Medical Studies (5114), Chiropractic (5101), and Dentistry (5104).

For the remaining two-digit categories, we calculate the total number of job postings shared among the four-digit majors contained in the two-digit category. Two-digit major categories that have few postings (less than 0.1%, or about 22,000 unique postings in our sample) are aggregated together as described below. For the large two-digit major categories we make a few general adjustments. First, we pull out some four-digit majors that are particularly large in terms of job postings. For example, in the two-digit category Architecture and Related Services (cip2=04), the four-digit major Architecture (cip4=0402) accounts for more than half of postings and degrees granted for the two-digit category. We thus split the two-digit category into the two *final major* groupings of (1) Architecture and (2) Urban and Regional Planning and Design. For the two-digit group Social Sciences (cip2=45), we disaggregate the four-digit majors of Sociology (cip4=4511), Economics (cip4=4506), and Geography (cip4=4507), all of which have large numbers of job postings and four-year degrees granted during 2010–2017, into three separate *final majors*, combine International Relations and National Security Studies (cip4=4509) and Political Science and Government (cip4=4510) into another *final major*, and aggregate most of the remaining four-digit majors into a *final major* called Other Social Sciences. As a final example, the 15 four-digit majors in the broad category of Education are grouped into three *final major* categories: (1) Special Education and Teaching, (2) Teacher Education, and (3) Other Education.

In some cases, pulling an individual four-digit major out of a two-digit category would result in an aggregation of the other remaining four-digit majors with a relatively small number of job postings. In these cases, we do not disaggregate the two-digit category; instead the two-digit category remains a *final major* category. For example, in the broad category of Family and Consumer Sciences & Human Sciences (19), the four-digit major Human Development, Family Studies, and Related Services (1907) constitutes over 86% of postings for the two-digit category, and the entire two-digit family becomes *final major* Family and Consumer Science. In other cases, although individual four-digit majors have both a large number of postings and degrees granted, the four-digit majors are commonly co-listed together on job postings. We aggregate these four-digit majors together into a *final major*. For example, within the two- digit category of Computer and Information Sciences and Support Services (11) the three most frequently occurring four-digit majors of Computer and Information Science, general (1101), Computer Science (1107), and Information Sciences/Studies (1104) are often listed on job postings together.

Finally, there are a few particular two-digit major categories that we split into more narrow *final major* categories, based on similarity of content or labor market outcomes. For example, in the broad category of Engineering there are over 39 four-digit majors which we aggregate into 10 *final major* categories including Mechanical Engineering, Computer Engineering, Electrical Engineering, and Civil Engineering. The 35 four-digit majors within the two-digit category Health Professions and Related Programs are aggregated into *final major* categories including Allied Health, Mental and Social Health Services, and Nursing.

We next deal with two-digit major categories that have few job postings, including Area, Ethnic, Cultural and Gender Studies (cip2=05), Communications Technologies/Technicians and Support Services (cip2=10), English Language and Literature/Letters (cip2=23), Liberal Arts and Sciences, General Studies Humanities (cip2=24), History (cip2=54) and Multi/Interdisciplinary Studies (cip2=30). To find the best fitting final major categories for each of these, we calculate the skill distance between the group and other four-digit majors. Generally, we use this method to find for each four-digit major the closest other four-digit majors, and assign it to the same *final major* category. Specifically, for each major we calculate the proportion of category postings for each of 8 skill composites ([# of ads with skill=*s* & majorcat=*c*]/[# of ads with majorcat=*c*]) on a sub-sample of our data. We then use the proportions to calculate a measure of cosine similarity: $\frac{\sum_{s}^{s=8}(a_i \times b_i)}{\sqrt{\sum_{s}^{s=8}(a_i)^2} \times \sqrt{\sum_{s}^{s=8}(b_i)^2}}$ where *a* and *b* are two different majors and a_i and b_i are the share of major *a*'s and major *b*'s postings that demand skill composite *i,* respectively. Finally, for a given major we sort other majors based on how similar skill demand is according to the cosine similarity measure. Using this method, we decided to combine the three two-digit majors of English, Liberal Arts and Humanities, and History into one *final major*, and the two-digit category Area Studies into the *final major* Other Social Sciences. We also used this method to find the most similar four-digit major for each of the majors in the fairly heterogeneous two-digit group of Multi/interdisciplinary Studies. As a result, we aggregated Systems Science and Theory (3006) into Management Information Systems and Science (5298), Museology/Museum Studies (3014) into Library Science (2500), and Behavioral Sciences (3017) into Psychology (4200).

Appendix B. Constructing Skill Composites

We initially followed the keyword approach of Deming and Kahn (2018) to allocate individual skills to skill composites. Our decision to reallocate individual skills to composites stemmed from three observations about the skill-to-composite mappings resulting from the keyword approach.

First, some of the most frequently listed skills did not fall into any skill composite. Examples include planning (20% of postings), organizational skills (16%), detail-oriented (12%), scheduling (12%), building effective relationships (11%), creativity (10%), troubleshooting (6%) and multi-tasking (8%).

Second, our use of the keyword approach meant that some skills were misclassified. The most prominent example is the case of using the keyword "management" to allocate skills to the skill composite "people management." The term "management" captures a wide variety of general management activities that do not specifically pertain to HR or personnel, including account management, pain management, operations management, case management, and management consulting. Another example was character (organizational) skills, which was initially defined as keywords "organized, detail-oriented, multitasking, time management, meeting deadlines, energetic" and as a result missed the very common variant skills of "multi-tasking" and "organizational skills".

Third, the ill-fitting mapping of skills to composites occurred for some of the most-frequent skills. In the case of relatively rare skills, misclassification of individual skills can be viewed as a form of measurement error that should not have a large impact on empirical results. However, since some individual skills are sufficiently common and get assigned to composites that seem incorrect *a priori*, we believe misclassification may bias the interpretation of a given skill composite. Thus, we focus on reallocating the individual skills that appear with the highest frequency.

We use the following procedure to map the 1,000 most frequent individual skills listed on job postings that demand a bachelor's degree to 11 skill composite categories. (The 1,000th most frequent skill appears on 0.2% of job postings that demand 16 years of education.) First, for each individual skill, two different individuals on the research team independently assigned the skill to one of the 11 categories according to the definition of the skill categories shown below. In roughly 40% of cases, two individuals assigned an individual skill to different skill composites.

For the 10 most frequent skills in which individual coding to composites differed, we discussed as a group which skill composite would be most fitting. We then refined our skill composition definitions, and pairs of individuals revisited and resolved cases in which a single skill was assigned to multiple skill composites. After this step there remained roughly 50 individual skills that pairs of reviewers still believed could fit into multiple categories. We allocated these skills to a single skill composite by consulting the occupation distribution of ads listing the skill. **Table 2** displays the final number of individual skills, and the three most frequent skills, allocated to each skill composite. **Appendix Table A3** shows the assigned skill composite for the 40 most frequently listed skills.

Skill Composite Definitions:

- **Social:** Communicating, persuading, or negotiating with others, which involves adept presentation or exchange of information and perspectives as well as the capacity to accurately infer the motivations of others.
- **People Management:** Supervising, motivating, or directing people internal to the business toward defined goals.
- **Cognitive:** Applying analytic, logical, quantitative or qualitative reasoning, evaluation, or critical thinking to understand patterns and solve problems.
- **Writing:** Composing, drafting, and editing of books, papers, reports, releases, scripts and other text-based documents; excludes underwriting (which is cognitive).
- **Customer Service/Client management:** Attracting, soliciting, maintaining, and retaining clients and customers; most forms of sales fall here if there is a personal contact (sales engineering or analysis is cognitive).
- **Organization:** Organizing, planning, managing, and expediting meetings, conferences, events, and other time-sensitive activities; but not logistics or supply chains (which are project management); ability to balance and prioritize among competing demands, apportion work, and meet deadlines.
- **Computer:** General computer tasks and knowledge, including MS Office and related frontline computer support; excludes computer engineering, hardware, design, and other specialized tasks.

- **Software:** Use or design of any specialized software, as well as any computer hardware design and engineering, and computer security or network management.
- **Financial:** Preparing or auditing payroll, budgets, accounting or tax documents, and financial reports and statements; excludes financial trading (social), financial engineering, or quantitative financial analysis (both cognitive)—the distinction is that the financial composite captures highly prescribed and rules-based activities that are often ancillary to main activities (unless the main activity is auditing/accounting).
- **Project Management:** Orchestrating, overseeing, or directing programs, projects, processes, and operations—the distinction with people and client management is that the emphasis here is not on people, but rather on the substance of the plans and activities executed by people.
- **Other:** Highly discipline-specific skills (often in health) or physical skills that do not readily generalize to other tasks.

Appendix C. Hand-Coded vs. Keyword Skill Composites

Our preferred approach to classifying skills was to assign by hand the 1,000 most frequent skills, as described above. This Appendix describes the sensitivity of our approach to the alternative of using the keywords displayed in Table 2 to identify skill composites.

A. Coverage

For all composites except software and people management, the share of ads assigned to the composite increases with our approach. About 1 in 500 postings do not list any of our 11 composites; this figure was closer to 1 in 25 based on the keyword approach, which covered only 8 composites. Notably, the keyword approach captured only 400 of the 1000 most frequent skills, while our preferred approach classifies all 1000. Preferred composites are now mutually exclusive: under the keyword approach, about 200 individual skills fell into more than one composite (70% of these involve software, and 30% involve customer service, people management, and cognitive).

The composites under our preferred approach capture a different number of individual, detailed skills than does the keyword approach. Under the latter system, for example, character (organization) contained only three detailed skills: “time management,” “meeting deadlines,” and “energetic.” Our preferred method also captures “multi-tasking,” “prioritizing tasks,” and “organizational skills.” This change means that some of the most common skills are now classified as “organizational skills,” as shown in the table below.

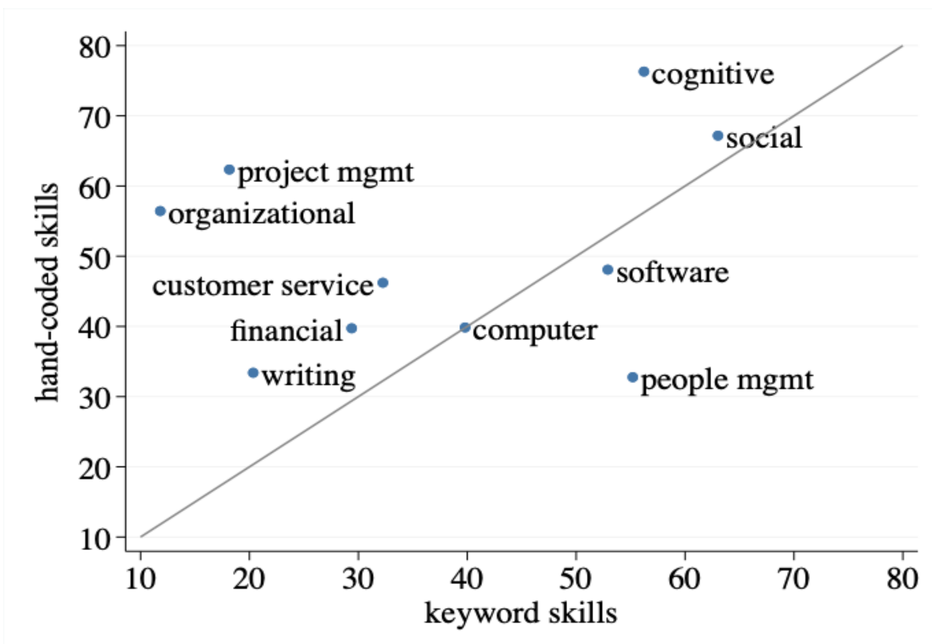
		Hand-coded		Keyword	
Skill composite number	Skill composite	Count of skills in 1000 most frequent	Count of skills across all skills	Count of skills in 1000 most frequent	Count of skills across all skills
1	social	56	56	15	78
2	people mgmt	43	43	85	476
3	cognitive	168	168	46	431
4	writing	20	20	8	50
5	customer service	110	110	56	372

6	organizational	37	37	3	3
7	computer	22	22	12	64
8	software	233	233	175	1703
9	financial	84	84	19	113
10	project mgmt	111	111	1	476
11	other	116	116		
	unclassified	0	14,260	602	12,081

B. Share of Ads in Each Composite

Figure A1 below compares the share of unique ads that contain each skill composite across the two different classification approaches.

Figure A1. Keyword (Old) vs Hand-coded (New) Skill Composites - % of Unique Ads



Note: Figure plots the percent of unique job postings that demand each skill composite. "Keyword" skills refer to the Deming & Kahn (2018) versions of the skill composites and "hand-coded" refers to the versions from Hemelt et al. (2021).

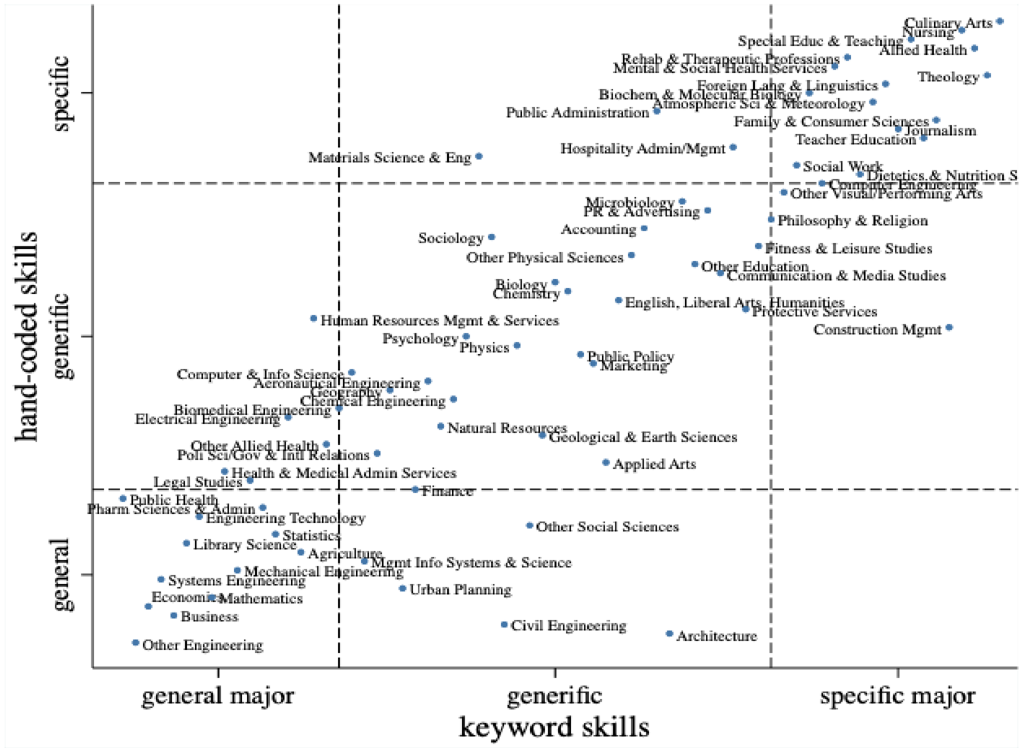
C. Characterization of Major Skill Concentration

Figure A2 compares our classification of major skill concentration between the two methods for classifying skills into composites. Panel A compares rank correlation between the two measures; 52 of 70 final majors stay in the same broad category (general, generific, specific) when shifting from the keyword approach to our preferred hand-coding approach.[1] Specifically, 12 majors are "general" (bottom left grouping) under both schemes, 24 stay "generific" (central grouping), and 16 stay "specific" (top right grouping). Nine majors become more specific when switching from the keyword to hand-coding method: for example, Biomedical Engineering and Legal, which move from "general" to "generific", and Material Sciences & Engineering and Public Administration, which move from "generific" to "specific." The last set of nine majors becomes more general, including Philosophy and Other Visual & Performing Arts, which move from "specific" to "generific," and Architecture and Other Social Sciences, which move from "generific" to "general." Panel B shows the specificity of selected majors under the two categorization systems in bar chart form.

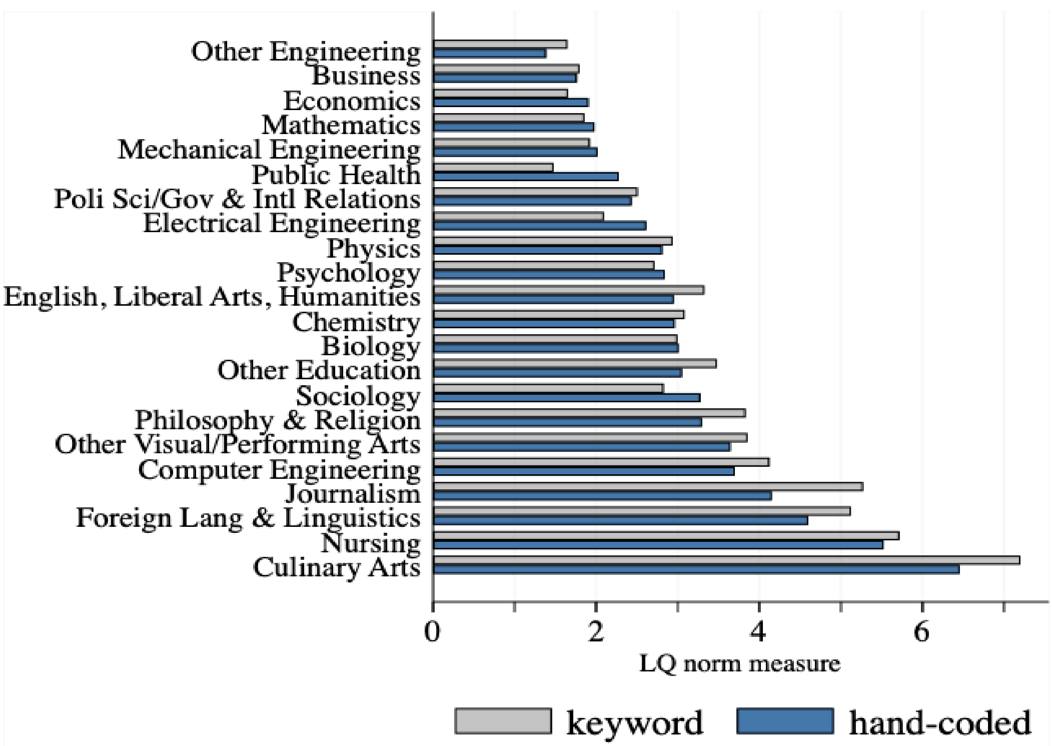
[1] The "general" category includes majors ranked 1 through 18 based on location quotient (LQ) similarity, "generific" includes those ranked 19 through 51, and "specific" includes those ranked 52 through 70. These roughly correspond to the top quartile, middle half, and bottom quartile of majors.

Figure A2. Skill Specificity of Majors Using Different Methods to Classify Skills

A. Rank Correlation



B. Measure of Skill Specificity



Appendix D. Replication of Deming and Kahn (2018)

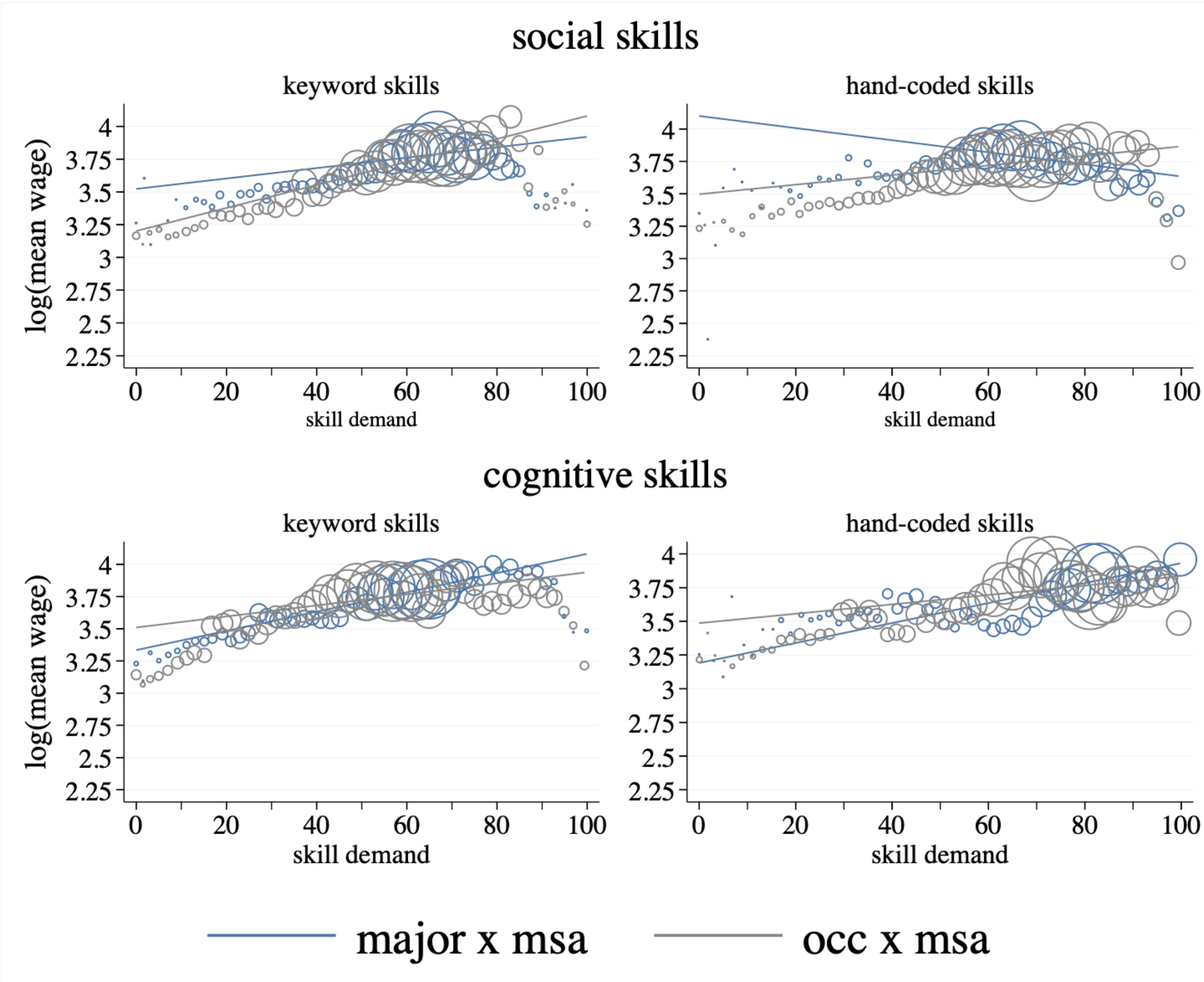
In order to better understand how our findings compare to those of Deming and Kahn (2018, DK), we attempt to replicate and extend their main cell-level analysis. DK regress log mean wages in a MSA-occupation cell on shares of job ads seeking cognitive skills, social skills, and their interaction. They control for average years of education and experience, the share of ads with each of eight other job skills, and an increasingly rich set of job characteristics, such as MSA and six-digit occupation fixed effects. Their main finding is that cognitive and social skill requirements are positively correlated with wages, both with and without rich controls. Their specification with the most complete set of controls finds that a 10 percentage point increase in the share of ads requiring cognitive (social) skills is associated with 0.8% (0.5%) higher wages. They conclude that skill requirements in local labor markets influence local wages even within narrowly defined occupations.

This conclusion contrasts with our finding of minimal association between skill requirements and major premia after netting out MSA and major fixed effects. These differences could stem from several factors, including the range of education levels considered in job postings, the years of job ad data included, the way in which skill composites are constructed, the vintage of the BGT data, the weighting scheme, and the type of aggregation (occupation vs. major). To assess the importance of these factors we replicate some of the main results found in DK's Table 3. Specifically, we follow DK and construct the log of average hourly earnings in MSA-by-six-digit-occupation cells using Occupation Employment Statistics (OES) data from 2012–2015. We then reconstruct the sample of job postings to match DK's by including job postings irrespective of the required education level. We collapse the data to MSA-by-occupation cells rather than MSA-by-major cells. Finally, we measure skill demand using both versions of the composites: the keyword approach used by DK and our hand-coded composites. **Table A10** presents our replication results.

We are able to replicate the main, fully controlled estimates reasonably well (column 1). Differences in the sample (column 3 vs. 1) have little influence on the estimates; however, the method for classifying skills does. Social skill requirements classified using the keyword approach have a positive association with earnings, but the association is zero or even negative when skills are hand-classified (columns 2 and 4). The final four columns report results for our sample, which aggregates ads into MSA-by-major cells and includes a full set of MSA and major fixed effects. We assess the importance of weighting and the classification method. The final column is quite similar to our preferred estimates in Table 5. The classification method and weighting scheme both matter. Estimates are closer to zero when we weight by incumbent workers (as measured in the ACS) rather than by job ads.

We were less successful in replicating the estimates from more parsimonious specifications in column 1 of DK's Table 3. However, in **Table A11** we present raw cell-level correlations between social and cognitive skill requirements and wages, where cells are constructed either by MSA-occupation or MSA-major. Cognitive skill requirements are consistently positively associated with cell-level wages regardless of aggregation process, weighting, or classification method. However, the patterns for social skills are not robust—the keyword approach generates positive associations with wages, but the hand-coding approach generates weaker or even negative associations. These patterns also appear in **Figure A3**, which presents scatter plots of cell-level skill demand and wages. This analysis reinforces our conclusion that the skill classification process, weighting scheme, and the manner in which ads are aggregated all contribute to differences between our results and those of DK. Further, the association between social skills and wages is much more sensitive to these choices than is the relationship between cognitive skills and wages.

Figure A3. Correlation between cell-level skill demand and wages



Note: Figure plots the binned averages of log(mean wage) across MSA-major (blue) and MSA-occupation (gray) cells. The cells for each category are divided into 50 bins, shown along the x-axis, based on the share of job postings in the cell that specify the indicated skill; each bin is thus two percentiles wide. The y-axis plots the average of log(mean wage) for all cells in the bin. A cell's log(mean wage) is the log of the average wage across individuals employed in the MSA-major or MSA-occupation, as captured in the ACS. Circles are sized based on the total number of job postings in the bin. "Keyword" skills refer to the skill composites from Deming & Kahn (2018) and "hand-coded" refers to the procedure described in the text.

Table A1. Explained Variation in Whether a Job Posting Lists at least One College Major

	(1)	(2)	(3)	(4)	(5)	(6)
Model SS	10928.4	12747.2	13138.9	21199.4	22288.4	25544.6
Residual SS	75920.3	74101.5	73709.7	65649.2	64560.2	61304.1
Total SS	86848.7	86848.7	86848.7	86848.7	86848.7	86848.7
R-squared	0.1258	0.1468	0.1513	0.2441	0.2566	0.2941
Adjusted R-squared	0.1218	0.1428	0.1473	0.2395	0.251	0.2722
Baseline variables	x	x	x	x	x	x
f(n skills)		x	x	x	x	x
Skill composites			x	x	x	x
500 most frequent skills				x		
1000 most frequent skills					x	
9000 most frequent skills						x
Number of variables	1611	1614	1625	2125	2624	10574
Number of skill dummies	0	0	0	500	999	8949
Observations	350,233	350,233	350,233	350,233	350,233	350,233

Note: The dependent variable is an indicator for whether or not a job posting lists at least one college major. For computational expedience, we use a 1% sample of all postings that require a bachelor's degree. The baseline variables include 941 metro- and micro- statistical region fixed effects, 99 year-by-month fixed effects, 504 six-digit occupation codes and 96 two-digit industry codes. F(skills) is a cubic in the number of skills per job posting.

Table A2: Has-Major F-Test

	Number of variables	Partial SS	F-test
Occupation (soc6)	482	7769.44	134.88***
Industry (naics2)	96	971.11	47.46***
Internship	1	84.13	386.52**
Year-by-month FEs	99	44.45	2.05***
Metro- / micro- statistical area	932	494.87	7.51***

Note: The table presents F-tests on blocks of covariates from a model in which an indicator for whether or not a job posting lists at least one college major is regressed on 941 metro- and micro- statistical region fixed effects, 99 year-by-month fixed effects, 504 six-digit occupation codes and 96 two-digit industry codes. Some fixed effects are omitted due to singleton observations. The sample is a 1% sample of all postings that require a bachelor's degree. Partial SS is the partial sum of squares from an ANOVA analysis of the baseline model and indicates the magnitude by which total sum of squares would decrease in a model that excludes the block of covariates.

Source: Authors' analysis of BGT job postings data.

Table A3. Categorization of 40 Most Frequently Listed Skills

	Individual Skill	Composite		Individual Skill	Composite
1	Communication Skills	social	21	Microsoft Word	computer
2	Planning	organization	22	Troubleshooting	cognitive
3	Microsoft Excel	computer	23	Accounting	financial
4	Teamwork / Collaboration	social	24	Multi-Tasking	organization
5	Problem Solving	cognitive	25	SQL	software
6	Organizational Skills	organization	26	Staff Management	people mgmt
7	Microsoft Office	computer	27	Customer Contact	customer service
8	Budgeting	financial	28	Presentation Skills	social
9	Research	cognitive	29	Quality Assurance and Control	project mgmt
10	Writing	writing	30	Time Management	organization
11	Project Management	project mgmt	31	Verbal / Oral Communication	social
12	Customer Service	customer service	32	Leadership	people mgmt
13	Sales	customer service	33	Software Development	software
14	Detail-Oriented	organization	34	Analytical Skills	cognitive
15	Written Communication	writing	35	Business Development	customer service
16	Scheduling	organization	36	Physical Abilities	other
17	Computer Literacy	computer	37	English	social
18	Building Effective Relationships	social	38	Patient Care	customer service
19	Creativity	cognitive	39	Oracle	software
20	Microsoft Powerpoint	computer	40	Teaching	social

Source: Authors' analysis of BGT job postings data.

Table A4. Complete List of Major Aggregates

Code	Name	Code	Name	Code	Name
0100	Agriculture	1600	Foreign Language and Linguistics	5098	Design, Photography, Video, and Applied Arts
0300	Natural Resources	1900	Family and Consumer Sciences	5099	Other Visual/Performing Arts
0402	Architecture	2200	Legal Studies	5107	Health and Medical Administrative Services
0499	Urban and Regional Planni	2499	English, Liberal Arts, Humanities	5109	Allied Health Diagnostic, Intervention, and Treatment Professions
0904	Journalism	2500	Library Science	5115	Mental and Social Health Services and Allied Professions
0909	Public Relations, Advertisi	2602	Biochemistry, Biophysics and Mo	5120	Pharmacy, Pharmaceutical Sciences, and Administration
0999	Communication and Media	2605	Microbiology	5122	Public Health
1100	Computer and Information	2699	Biology	5123	Rehabilitation and Therapeutic Professions
1205	Culinary Arts	2705	Statistics	5131	Dietetics and Clinical Nutrition Services
1310	Special Education and Teac	2799	Mathematics	5138	Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing
1398	Teacher Education	3100	Fitness, Recreation and Leisure St	5199	Allied Health
1399	Other Education	3800	Philosophy and Religion	5203	Accounting and Related Services
1402	Aeronautical Engineering	3900	Theology	5208	Finance and Financial Management Services
1405	Biomedical Engineering	4004	Atmospheric Sciences and Meteor	5209	Hospitality Administration/Management
1407	Chemical Engineering	4005	Chemistry	5210	Human Resources Management and Services
1408	Civil Engineering	4006	Geological and Earth Sciences/Ge	5214	Marketing
1409	Computer Engineering	4008	Physics	5220	Construction Management
1410	Electrical, Electronics and	4019	Materials Science and Engineering	5298	Management Information Systems and Science
1419	Mechanical Engineering	4099	Other Physical Sciences	5299	Business, general
1497	Systems, Industrial, Manuf	4200	Psychology		
1499	Other Engineering	4300	Protective Services		
1500	Engineering technology	4404	Public Administration		
		4405	Public Policy		
		4407	Social Work		
		4506	Economics		
		4507	Geography		
		4510	Political Science, Government, and International Relations		
		4511	Sociology		
		4599	Other Social Sciences		

Table A5. Top Skills Associated with Three Majors

Economics Majors		Teacher Education Majors		Journalism Majors	
Skill	% of postings	Skill	% of postings	Skill	% of postings
Economics	0.989	Early Childhood Education	0.682	Journalism	1.000
Communication Skills	0.523	Teaching	0.622	Writing	0.672
Microsoft Excel	0.464	Child Development	0.456	Editing	0.623
Research	0.328	Child Care	0.432	Communication Skills	0.511
Planning	0.254	Organizational Skills	0.308	Creativity	0.412
Problem Solving	0.25	Communication Skills	0.284	Social Media	0.394
Accounting	0.241	Lesson Planning	0.256	Research	0.323
Teamwork / Collaboration	0.237	Health Education	0.187	Teamwork / Collaboration	0.299
Microsoft Powerpoint	0.21	Planning	0.181	Organizational Skills	0.264
Budgeting	0.206	Teamwork / Collaboration	0.166	Detail-Oriented	0.254
N(ads)	607,518	N(ads)	97,314	N(ads)	211,471

Source: Authors' analysis of BGT job postings.

Table A6. Share of Ads for Each Major Indicating Demand for Each Skill Composite

Major	Code	Cognitive	Social	Project Management	Organizational	Software	Customer Service	Computer	Financial	Writing	People Management	Communications Skills	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%	38%	78%
Agriculture	100	80%	66%	64%	58%	13%	43%	48%	47%	26%	37%	44%	58%	79%
Natural Resources	300	91%	64%	60%	66%	21%	29%	42%	42%	52%	37%	45%	59%	93%
Architecture	402	75%	66%	69%	73%	62%	30%	45%	46%	34%	30%	42%	34%	88%
Urban Planning	499	81%	68%	63%	87%	38%	32%	47%	47%	48%	31%	43%	46%	100%
Journalism	904	76%	90%	44%	74%	34%	40%	47%	21%	100%	26%	51%	35%	85%
PR & Advertising	909	80%	93%	56%	76%	31%	65%	52%	34%	70%	30%	56%	32%	85%
Communication & Media Stu	999	77%	90%	58%	73%	37%	60%	52%	31%	70%	32%	56%	31%	82%
Computer & Info Science	1100	82%	65%	70%	50%	94%	39%	27%	19%	36%	29%	47%	25%	84%
Culinary Arts	1205	60%	43%	34%	65%	1%	48%	56%	75%	12%	68%	20%	93%	40%
Special Educ & Teaching	1310	66%	89%	20%	47%	4%	40%	20%	16%	31%	39%	29%	100%	72%
Teacher Education	1398	60%	99%	24%	57%	4%	61%	22%	17%	24%	34%	28%	40%	51%
Other Education	1399	92%	88%	68%	62%	47%	33%	52%	25%	54%	66%	63%	39%	88%
Aeronautical Engineering	1402	91%	57%	57%	48%	57%	24%	32%	23%	33%	21%	44%	49%	87%
Biomedical Engineering	1405	94%	63%	68%	50%	46%	31%	31%	24%	35%	23%	44%	69%	99%
Chemical Engineering	1407	100%	60%	80%	44%	23%	35%	32%	35%	29%	27%	44%	48%	86%
Civil Engineering	1408	97%	54%	61%	60%	43%	29%	37%	46%	39%	29%	39%	44%	88%
Computer Engineering	1409	80%	60%	63%	44%	100%	29%	19%	12%	33%	23%	44%	27%	86%
Electrical Engineering	1410	84%	58%	63%	46%	73%	30%	27%	25%	32%	22%	43%	45%	88%
Mechanical Engineering	1419	94%	58%	72%	51%	48%	31%	38%	37%	30%	25%	43%	56%	84%
Systems Engineering	1497	94%	65%	86%	57%	68%	33%	43%	34%	32%	32%	50%	56%	83%
Other Engineering	1499	83%	61%	74%	54%	57%	36%	34%	35%	33%	31%	44%	44%	83%
Engineering Technology	1500	85%	57%	77%	56%	37%	28%	39%	40%	32%	41%	40%	62%	89%
Foreign Lang & Linguistics	1600	61%	90%	30%	39%	23%	16%	27%	15%	44%	17%	28%	30%	84%
Family & Consumer Sciences	1900	64%	95%	21%	60%	5%	73%	20%	20%	21%	36%	25%	38%	50%
Legal Studies	2200	69%	67%	44%	66%	15%	40%	38%	54%	50%	33%	42%	33%	74%
English, Liberal Arts, Human	2499	73%	84%	40%	60%	26%	36%	44%	26%	60%	25%	44%	32%	75%
Library Science	2500	78%	79%	43%	65%	40%	31%	46%	31%	49%	38%	48%	39%	80%
Biochem & Molecular Biolog	2602	99%	64%	44%	55%	14%	21%	32%	17%	35%	16%	49%	87%	97%
Microbiology	2605	100%	58%	69%	49%	13%	25%	36%	29%	32%	29%	39%	77%	90%
Biology	2699	91%	61%	54%	51%	24%	29%	35%	26%	36%	27%	41%	69%	93%
Statistics	2705	97%	74%	69%	55%	75%	39%	55%	34%	37%	26%	51%	26%	84%
Mathematics	2799	92%	66%	67%	53%	78%	34%	42%	28%	37%	27%	47%	27%	82%

Table A6. Share of Ads for Each Major Indicating Demand for Each Skill Composite

Major	Code	Cognitive	Social	Project Management	Organizational	Software	Customer Service	Computer	Financial	Writing	People Management	Communications Skills	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%	38%	78%
Fitness & Leisure Studies	3100	49%	74%	37%	53%	17%	50%	34%	26%	26%	41%	41%	55%	77%
Philosophy & Religion	3800	70%	74%	35%	46%	21%	19%	22%	23%	36%	31%	34%	30%	70%
Theology	3900	31%	68%	15%	38%	3%	51%	21%	12%	20%	22%	36%	27%	47%
Atmospheric Sci & Meteorolo	4004	63%	64%	26%	44%	25%	15%	24%	11%	52%	17%	33%	45%	100%
Chemistry	4005	100%	57%	65%	49%	15%	30%	36%	27%	33%	27%	42%	60%	87%
Geological & Earth Sciences	4006	89%	53%	60%	58%	27%	30%	30%	37%	46%	35%	35%	55%	94%
Physics	4008	100%	58%	60%	43%	67%	29%	24%	18%	34%	24%	41%	37%	83%
Materials Science & Eng	4019	94%	62%	72%	43%	25%	31%	31%	26%	30%	23%	47%	90%	87%
Other Physical Sciences	4099	90%	53%	56%	54%	27%	22%	22%	25%	38%	41%	35%	56%	89%
Psychology	4200	87%	79%	42%	55%	17%	58%	36%	22%	34%	44%	39%	50%	74%
Protective Services	4300	72%	59%	50%	50%	23%	28%	33%	36%	40%	35%	33%	72%	84%
Public Administration	4404	75%	69%	79%	70%	23%	38%	43%	67%	49%	55%	36%	100%	76%
Public Policy	4405	86%	85%	71%	73%	28%	39%	49%	45%	67%	38%	59%	46%	83%
Social Work	4407	70%	74%	34%	54%	4%	78%	32%	21%	31%	38%	32%	54%	64%
Economics	4506	100%	75%	68%	64%	45%	44%	60%	61%	39%	30%	52%	30%	79%
Geography	4507	82%	62%	50%	61%	72%	35%	41%	20%	50%	20%	42%	31%	97%
Poli Sci/Gov & Intl Relations	4510	82%	80%	56%	68%	25%	35%	45%	40%	60%	37%	49%	47%	78%
Sociology	4511	96%	76%	42%	58%	14%	65%	38%	26%	37%	48%	34%	58%	74%
Other Social Sciences	4599	86%	72%	50%	63%	30%	32%	37%	31%	51%	31%	38%	41%	91%
Applied Arts	5098	94%	87%	52%	66%	77%	45%	40%	22%	36%	17%	46%	39%	92%
Other Visual/Performing Arts	5099	76%	83%	37%	66%	61%	29%	32%	19%	59%	18%	42%	51%	95%
Health & Medical Admin Ser	5107	75%	69%	84%	58%	26%	67%	45%	53%	37%	51%	44%	47%	75%
Allied Health	5109	52%	56%	38%	38%	8%	67%	23%	18%	18%	30%	27%	82%	96%
Mental & Social Health Servi	5115	57%	98%	28%	43%	4%	75%	27%	13%	26%	39%	25%	65%	68%
Pharm Sciences & Admin	5120	75%	74%	67%	50%	13%	55%	35%	35%	38%	38%	52%	51%	85%
Public Health	5122	77%	74%	98%	58%	22%	48%	44%	39%	44%	43%	46%	53%	84%
Rehab & Therapeutic Profess	5123	56%	67%	34%	46%	4%	76%	19%	27%	22%	67%	29%	54%	87%
Dietetics & Nutrition Service:	5131	42%	67%	36%	58%	6%	60%	33%	26%	18%	31%	28%	54%	91%
Nursing	5138	47%	60%	31%	49%	4%	82%	23%	16%	14%	36%	30%	70%	62%
Other Allied Health	5199	72%	64%	73%	51%	22%	61%	39%	39%	29%	43%	41%	58%	75%
Accounting	5203	73%	61%	52%	62%	35%	33%	62%	92%	30%	28%	46%	28%	68%
Finance	5208	82%	68%	62%	64%	40%	39%	63%	82%	32%	29%	50%	30%	71%

Table A6. Share of Ads for Each Major Indicating Demand for Each Skill Composite

Major	Code	Cognitive	Social	Project Management	Organizational	Software	Customer Service	Computer	Financial	Writing	People Management	Communications Skills	Other Skills (top 1000)	Other Skills (< top 1000)
All postings	0	80%	68%	65%	58%	50%	46%	42%	43%	35%	33%	46%	38%	78%
Hospitality Admin/Mgmt	5209	59%	74%	75%	68%	9%	64%	47%	61%	27%	65%	41%	54%	62%
Human Resources Mgmt & S	5210	69%	81%	66%	66%	37%	33%	60%	43%	36%	76%	55%	31%	73%
Marketing	5214	79%	89%	67%	69%	33%	84%	52%	37%	49%	35%	56%	30%	79%
Construction Mgmt	5220	77%	64%	100%	79%	29%	33%	59%	70%	34%	37%	43%	41%	76%
Mgmt Info Systems & Scienc	5298	88%	68%	78%	57%	96%	45%	38%	31%	40%	36%	50%	29%	81%
Business	5299	78%	77%	77%	65%	40%	56%	51%	56%	36%	43%	53%	35%	75%
Minimum		31%	43%	15%	38%	1%	15%	19%	11%	12%	16%	20%	25%	40%
Maximum		100%	99%	100%	87%	100%	84%	63%	92%	100%	76%	63%	100%	100%
Mean		79%	70%	56%	57%	33%	42%	38%	34%	38%	34%	42%	49%	81%
Standard Deviation		15%	12%	19%	10%	24%	17%	12%	17%	14%	12%	9%	18%	12%

Note: Mean and standard deviation are calculated equally weighting 70 majors.

Source: Authors' analysis of BGT job postings data.

Table A7. Correlation between Different Measures of Major Skill Specificity

	A. Outcome = Similarity based on 9000 skills				B. Outcome = LQ measure			
	Rank		Measure		Rank		Measure	
Outcome	No weight	weighted	No weight	weighted	No weight	weighted	No weight	weighted
LQ measure (only top 1000 skills)	0.372	0.533	0.410	0.573				
Similarity (Full)					0.372	0.533	0.410	0.573
Similarity (top 1000)	0.895	0.964	0.896	0.989	0.358	0.579	0.388	0.579
Similarity (1001+)	0.320	0.474	0.300	0.563	0.166	0.374	0.195	0.374
% of recent grads in top 5 occupations	0.050	0.317	0.075	0.342	0.004	0.469	0.019	0.469

Note: “Full similarity” is the cosine similarity (or rank) of a major using all 9000 skills. Top 1000 is the cosine similarity using only the 1000 most frequent skills. 1001+ is cosine similarity using skills ranked 1001-9000 in terms of overall frequency. LQ is location quotient across 11 skill composites (calculated as sum(abs(LQ-1) across the composites) and expressed in either rank or actual measure. Percent of recent graduates in top 5 occupations measures the fraction of a major’s graduates aged 23-27 that are found in the 5 most frequent occupations for the major in the ACS.

Panel A regresses a major’s rank (measure) for the full similarity on the rank (measure) of the variable in the first column. Panel B does the same but with outcomes based on sum(abs(LQ-1)). Each regression has 70 observations (1 for each major) except for % in top 5 occupations which has 66 observations because 4 majors are missing from the ACS. Each cell is the adjusted R-squared from the regression. In weighted regressions, majors are weighted by the number of job postings.

Source: Authors' analysis of BGT job postings and ACS data.

Table A8. Comparison of Major Rankings by Measure of Specificity

	LQ-based rank	Cosine-based rank	Gini-based rank
Most specific	Culinary Arts	Family & Consumer Sciences	Primary/General Education
(top 10)	Nursing	Special Education & Teaching	Secondary Education
	Special Education & Teaching	Mental & Social Health Services	Nursing
	Allied Health	Teacher Education	Medical Tech
	Rehab & Therapeutic Professions	Atmospheric Science & Meteorology	Computer Programming
	Mental & Social Health Services	Culinary Arts	Other Med/Health Services
	Theology	Microbiology	Finance
	Foreign Language & Linguistics	Rehab & Therapeutic Professions	Precision Production/Industrial Arts
	Biochem & Molecular Biology	Biochem & Molecular Biology	Commercial Art and Design
	Atmospheric Science & Meteorology	Allied Health	Marketing
Most general	Other Engineering	Business	Music/Speech/Drama
(top 10)	Architecture	Other Engineering	Other Social Sciences
	Civil Engineering	Marketing	Philosophy/Religion
	Business	Other Allied Health	Environmental Studies
	Economics	Library Science	Psychology
	Mathematics	Health & Medical Admin Services	Accounting
	Urban Planning	Pharmacy Sciences & Administration	Area Studies
	Systems Engineering	Legal Studies	Social Work/Human Resources
	Mechanical Engineering	Mathematics	Mathematics
	Management Information Systems & Science	Political Science, Government, International Relations	Engineering Tech

Notes: This table mirrors the layout of Table 3 in Leighton and Speer (2020), comparing the top and bottom 10 majors in terms of specificity based on different measures: thus, majors in the "Most specific" panel are listed from most specific to least specific; majors in the "Most general" panel are listed from least specific (i.e., most general) to more specific. Our two ranking measures appear in italics. Rankings in the Gini-based column come from Table 3 in Leighton and Speer (2020).

Table A9. Major Specific Skill Similarity Measures

Major	Code	% of unique postings	% of posting x major	cosine similarity	LQ norm measure 1	LQ norm measure 2
Agriculture	100	0.815	0.483	0.777	2.048	0.961
Natural Resources	300	0.353	0.209	0.712	2.547	1.076
Architecture	402	0.34	0.201	0.697	1.409	0.29
Urban Planning	499	0.235	0.14	0.721	1.984	0.612
Journalism	904	1.145	0.679	0.597	4.154	4.112
PR & Advertising	909	1.014	0.601	0.797	3.314	1.691
Communication & Media Stu	999	2.569	1.523	0.82	3.041	1.512
Computer & Info Science	1100	26.149	15.504	0.792	2.701	1.375
Culinary Arts	1205	0.19	0.113	0.457	6.458	5.643
Special Educ & Teaching	1310	0.216	0.128	0.405	5.447	4.819
Teacher Education	1398	0.527	0.312	0.439	4.045	2.313
Other Education	1399	0.28	0.166	0.719	3.052	1.631
Aeronautical Engineering	1402	0.444	0.263	0.73	2.686	0.858
Biomedical Engineering	1405	0.186	0.11	0.624	2.642	1.174
Chemical Engineering	1407	0.609	0.361	0.561	2.643	0.748
Civil Engineering	1408	0.953	0.565	0.57	1.633	0.324
Computer Engineering	1409	2.483	1.472	0.545	3.701	2.2
Electrical Engineering	1410	5.726	3.395	0.815	2.615	0.844
Mechanical Engineering	1419	4.288	2.543	0.739	2.018	0.516
Systems Engineering	1497	0.678	0.402	0.817	1.993	0.602
Other Engineering	1499	16.459	9.759	0.922	1.388	0.209
Engineering Technology	1500	0.877	0.52	0.798	2.16	0.744
Foreign Lang & Linguistics	1600	0.113	0.067	0.627	4.599	2.189
Family & Consumer Sciences	1900	0.375	0.222	0.394	4.348	2.537
Legal Studies	2200	0.729	0.432	0.849	2.394	0.95
English, Liberal Arts, Human	2499	0.138	0.082	0.839	2.955	1.211
Library Science	2500	0.111	0.066	0.872	2.072	0.56
Biochem & Molecular Biolog	2602	0.177	0.105	0.511	4.583	3.276
Microbiology	2605	0.435	0.258	0.498	3.491	2.023
Biology	2699	1.397	0.829	0.718	3.011	1.356
Statistics	2705	1.683	0.998	0.781	2.143	0.626
Mathematics	2799	2.204	1.307	0.847	1.982	0.634
Fitness & Leisure Studies	3100	0.365	0.216	0.809	3.246	1.301
Philosophy & Religion	3800	0.02	0.012	0.777	3.297	1.448
Theology	3900	0.068	0.04	0.717	5.089	3.141
Atmospheric Sci & Meteorolo	4004	0.03	0.018	0.453	4.57	2.374
Chemistry	4005	1.768	1.048	0.568	2.965	1.245
Geological & Earth Sciences	4006	0.477	0.283	0.591	2.435	0.788
Physics	4008	0.894	0.53	0.571	2.81	1.006
Materials Science & Eng	4019	0.173	0.103	0.582	3.938	2.678
Other Physical Sciences	4099	0.027	0.016	0.606	3.206	1.231
Psychology	4200	1.408	0.835	0.663	2.841	1.109
Protective Services	4300	0.112	0.067	0.697	2.949	1.402
Public Administration	4404	0.772	0.458	0.631	4.411	3.902
Public Policy	4405	0.156	0.093	0.842	2.747	1.282
Social Work	4407	1.559	0.925	0.62	3.814	2.119
Economics	4506	3.289	1.95	0.728	1.907	0.535
Geography	4507	0.169	0.1	0.681	2.643	0.962
Poli Sci/Gov & Intl Relations	4510	0.332	0.197	0.847	2.433	0.972
Sociology	4511	0.393	0.233	0.609	3.277	1.469
Other Social Sciences	4599	0.107	0.064	0.758	2.147	0.629
Applied Arts	5098	1.005	0.596	0.594	2.429	0.937
Other Visual/Performing Arts	5099	0.098	0.058	0.62	3.647	1.56

Table A9. Major Specific Skill Similarity Measures

Major	Code	% of unique postings	% of posting x major	cosine similarity	LQ norm measure 1	LQ norm measure 2
Health & Medical Admin Ser	5107	0.951	0.564	0.861	2.411	0.922
Allied Health	5109	0.1	0.059	0.514	5.389	3.501
Mental & Social Health Servi	5115	0.073	0.043	0.408	5.282	3.096
Pharm Sciences & Admin	5120	0.229	0.136	0.856	2.162	0.822
Public Health	5122	0.915	0.542	0.737	2.28	0.88
Rehab & Therapeutic Profess	5123	0.312	0.185	0.506	5.312	3.409
Dietetics & Nutrition Service	5131	0.29	0.172	0.587	3.772	1.948
Nursing	5138	8.424	4.995	0.621	5.525	3.626
Other Allied Health	5199	2.402	1.424	0.876	2.434	0.865
Accounting	5203	13.867	8.222	0.731	3.285	1.94
Finance	5208	11.152	6.612	0.825	2.381	1.238
Hospitality Admin/Mgmt	5209	0.255	0.151	0.809	4.023	2.292
Human Resources Mgmt & S	5210	2.076	1.231	0.817	2.921	2.085
Marketing	5214	5.567	3.301	0.88	2.716	1.202
Construction Mgmt	5220	0.906	0.537	0.629	2.908	1.242
Mgmt Info Systems & Scienc	5298	4.485	2.659	0.749	2.041	1.047
Business	5299	29.535	17.512	0.958	1.764	0.375

Note: For each major, cosine similarity is constructed using the major’s vector of share of all ads listing each of the 9,000 most common skills and the national vector using the same skills.
For each major, LQ norm measure 1 is calculated as the sum across all 11 skill composites of the absolute value of the deviations of the LQs from 1.
For each major, LQ norm measure 1 is calculated as the sum across all 11 skill composites of the squared deviations of the LQs from 1.
Source: Authors' analysis of BGT job postings data.

Table A10. Replication and Extension of Deming & Kahn (2018)

		Replication: Occupation-MSA Cell				Our sample: Major-MSA Cells			
		All education levels		Education = 16		Education = 16		Education = 16	
	DK estimates	Keyword	Hand code	Keyword	Hand code	Keyword	Hand code	Keyword	Hand code
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share cognitive	0.0792***	0.0484	0.0601*	0.0359	0.0593*	-0.0021	0.125*	0.0076	-0.0049
		(0.0357)	(0.0341)	(0.0303)	(0.0345)	(0.0519)	(0.0685)	(0.0193)	(0.0246)
Share social	0.0517***	0.0508*	-0.0129	0.0566*	0.0174	0.0642	0.0509	-0.0123	0.0090
		(0.0264)	(0.0385)	(0.0328)	(0.0149)	(0.0422)	(0.0438)	(0.0169)	(0.0199)
Observations		54,216	54,216	43,848	43,848	22,151	22,151	22,151	22,151
Controls	6-digit occ FE, MSA FE, % of postings in 2 digit industry, education, experience					Major FE, MSA FE			
Outcome		log(mean hourly wage) from OES				log(mean hourly wage) from ACS			
Weights		Job postings from BG				Job postings from BG		Person wt from ACS	

Notes: DK estimates are from Table 3 column 5 of Deming & Kahn (2018). All models also include the share of ads in each cell that require customer service, financial, organizational, people management, project management, writing, basic computer, and software skills.

Table A11. Raw cell-level correlations between social and cognitive skill content and wages, Robustness

	MSA x major	MSA x occ	MSA x major	MSA x occ	MSA x major	MSA x occ
	(1)	(2)	(3)	(4)	(5)	(6)
Share cognitive						
Keyword	0.855***	0.569***	0.399***	0.290***	0.746***	0.430***
	(0.0101)	(0.0089)	(0.0106)	(0.0067)	(0.0114)	(0.0090)
Handcode	0.498***	0.359***	0.417***	0.187***	0.745***	0.347***
	(0.0122)	(0.0092)	(0.0112)	(0.0068)	(0.0122)	(0.0094)
Share social						
Keyword	0.205***	0.688***	0.141***	0.257***	0.394***	0.875***
	(0.0130)	(0.0104)	(0.0120)	(0.0072)	(0.0146)	(0.0113)
Handcode	-0.601***	0.0222**	-0.282***	-0.0459***	-0.464***	0.369***
	(0.0126)	(0.0112)	(0.0121)	(0.0073)	(0.0137)	(0.0115)
Weights	ACS perwt	soc emp	none	none	postings	postings
Observations	22,151	43,852	22,151	43,852	22,151	43,852

Notes: Each cell is a separate regression of cell-level log mean wages (major-MSA or occupation-MSA) on the share of ads requiring each skill.